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Agent based modeling of *Eciton burchelli* swarm patterns

Jose Almora [£],
Albert Izarraraz [†],
Qiao Liang [‡],
Crystal Nesmith [§]
David Murillo [◇]

[£] University of North Carolina Chapel Hill, jalmora@email.unc.edu
[†] University of California Irvine, aizarrar@uci.edu
[‡] University of New Mexico Albuquerque, rabbit@unm.edu
[§] St. Mary's College of Maryland, cnnesmith@smcm.edu
[◇] Arizona State University, dlm35@mathpost.asu.edu

Eciton burchelli are a unique species of army ants that demonstrate distinctive swarm behavior. We observe their reactions to different initial food distributions in a simulated ant world and determine the stability of their swarm patterns to perturbations and external factors. The first step is to recover the swarm behavior observed in nature using the simplest behavioral rules. Then we investigate the impact of disruptions to the pheromone trails on the emergent behavior of ants through agent based simulations. The poor vision of *E. burchelli* make pheromone trails a key element to the survival of the colony.

Their are several scenarios for swarm pattern formation including a single food source, multiple food sources, and perturbations to the multiple food sources implemented by randomly placing barriers over established trails. This is done through agent based simulations that allow us to visualize the development of ant swarms.

In addition to the simulations, we propose a modified version of Fisher's Equation to demonstrate ant swarm behavior at the swarm front from a theoretical point-of-view. The basic Fisher's Equation has a traveling wave solution that integrates the logistic growth and diffusion of the ants' population density. We add a taxis and removal rate into the equation to include pheromone trail drift and loss of population during a swarm. Taxis is due to ant attraction to the food sources, and removal is due to death and deviation from the trail. The equation we propose is:

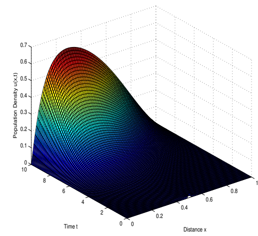
$$\frac{du}{dt} = ru(1-u) - \nu_1 + (\alpha_1 + \beta_1 u)\frac{\partial u}{\partial x} + D_1 \frac{\partial^2 u}{\partial x^2}, \qquad (1)$$

where u is the population density, t is time, $D1$ is the diffusion coefficient, r is the intrinsic growth rate, α is the drifting velocity, β is the density dependent taxis, and ν_1 is the removal rate. A solution to Equation 1 is shown in Figure 1, and we see that the population grows and drifts at the same time.

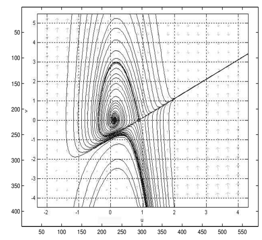
Analysis of the wave solutions to equation 1 yield a hopf bifurcation, creating a limit cycle that can collide into a homoclinic orbit, see Figure 2.

The question we will answer with the numerical simulations is whether external factors, such as obstacles, affect pheromone trails and swarm pattern formation. An agent-based model allows us to specify rules for individual ants and their interactions with the environment and themselves. We first create the simplest set of rules that will generate complex swarm patterns and then monitor the impact of different environmental factors on these patterns. The rules are as follows:

- Ants can move randomly with a large bias towards the forward direction.
- When searching for food, they exhibit a behavior called the rebound effect. They explore forward several steps and if no food is found, they will backtrack a few steps and possibly change direction.



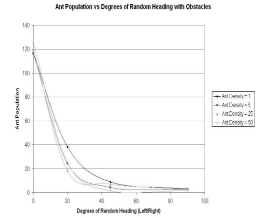
Evolution of the density with taxis as a function of time and space



Limit cycle approaches a homoclinic orbit

- If food is discovered, a large concentration of pheromone will be deposited to attract more ants.
- When returning with food, the ants lay a type of pheromone which recruits other ants to gather more food. To avoid overcrowding, they will branch out around the food source, consuming it more efficiently.

The three categories of simulations are: single food source, and multiple food sources with or without obstacles added half way through the simulation. Our benchmarks are the final population size (we run each simulation for 5 minutes) and the amount of food gathered. These benchmarks are independent to density (how likely the ants are to spread out around the food source), but highly dependent on the degree of randomness in ant movement. When they have a high probability of turning, they stray off the pheromone trail and have difficulty finding food. However, a certain amount of randomness is essential to the discovery of alternate food sources since the main food source can run out or the primary trail can get perturbed. They usually produce one main swarm and a few sub-swarms with increased randomness.



Ant population with respect to randomness in environment with obstacles

Obstacles have a major impact on the population size of the ants, see Figure 3, and nearly causes extinction in many cases. However, in real life the ants can overcome most minor obstacles and establish new trails, but here we assume obstacles are cannot be overcome and examples include destruction or major alteration of the landscape or active interference. This is analogous to human invasion of ant habitats and supports the need for conservation biology.

Modeling a natural phenomenon such as ant swarms with sophisticated mathematical equations and advanced simulations provide a closer look as to how things work. The analysis can be refined to the point of quantitatively deriving the inner workings of a complex system such as an ant swarm. This project enabled us to study localized behavior of a self-organizing species.

The two approaches, modified Fisher's Equation and agent-based modeling, concentrate on separate parts of the army ant swarm patterns. The two different forms of analysis provide various insights when studying the swarm behaviors. The two methods applied produce a substantial amount of information on the complexity of self-organizing systems. The approaches used can be applied to other types of self-organizing systems such as bees, termites, and fish. These studies lead to greater understanding of the systems, which provides a window of reflection based on our own behavior.

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